Dynamic Network Strategies for SARS-CoV-2 Control on a Cruise Ship

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Supplemental Appendix

1 INTRODUCTION

This supplementary technical appendix describes the mathematical model structure, parameterization, and statistical analysis of the accompanying paper in further detail.

1.1 Model Framework

The mathematical models for SARS-CoV-2 transmission dynamics presented in this study are network-based transmission models in which uniquely identifiable relational contact dyads were simulated and tracked over time. This contact structure is represented through the use of temporal exponential-family random graph models (TERGMs). On top of this dynamic network simulation, the epidemic model represents demography (exits, and aging), interhost epidemiology (disease transmission), intrahost epidemiology (disease progression), and clinical epidemiology (disease diagnosis and treatment and prevention interventions). Individual attributes related to these processes are stored and updated in discrete time over the course of each epidemic simulation.

1.2 Model Software

The models in this study were programmed in the R and C++ software languages using the *EpiModel* [http://epimodel.org/] software platform for epidemic modeling. *EpiModel* was developed by the authors for simulating complex network-based mathematical models of infectious diseases.(1) *EpiModel* depends on *Statnet* [http://statnet.org/], a suite of software in R for the representation, visualization, and statistical analysis of complex network data.(2)

EpiModel allows for a modular expansion of its built-in modeling tools to address novel research questions. We have developed a set of extension modules into a software package called *EpiModelCOVID*. This software is available for download, along with the scripts used in the execution of these models. The tools and scripts to run these models are contained in two GitHub repositories:

- [http://github.com/EpiModel/EpiModelCOVID] contains the general extension software package. Installing this using the instructions listed at the repository homepage will also load in *EpiModel* and the other dependencies.
- [http://github.com/EpiModel/COVIDCruiseShip] contains the scripts to execute the models and to run the statistical analyses provided in the manuscript.

1.3 Core Model Specifications

We started with a network size of 3711 persons on the Diamond Princess Cruise Ship. Age was represented as a continuous attribute, with initial distributions drawn from empirical distributions: passengers averaged 69 years old (interquartile range: 62–73) and crew averaged 36 years old (interquartile range: 29–43). The network size was allowed to decrease with departures related to mortality. We used a two-stage simulation framework, first calibrating the model to diagnosed cases on the ship (Stage 1), and then simulating the reference and counterfactual intervention scenarios for 30

days in most scenarios. The time unit used throughout the simulations was one day. Unless otherwise noted, all rate-based parameters listed below are to be interpreted as the rate per day and all duration-based estimates are to be interpreted as the duration in days.

2 NETWORKS OF SOCIAL CONTACTS

We modeled networks of three interacting types of network contacts relations: passenger to passenger, passenger to crew, and crew to crew. We first describe the methods conceptually, including the parameters used to guide the model and their derivation, and then present the formal statistical modeling methods. Consistent with our parameter derivations, all contacts are defined as those in which respiratory exposure is expected to occur at least once.

2.1 Conceptual Representation of Networks

Our modeling methods aim to preserve certain features of the cross-sectional and dynamic network structure as observed in our primary data, while also allowing for mean contact durations to be targeted to those reported for different groups and relational types. Our methods do so within the context of changing population size (due to deaths and departures from the population) and changing composition by attributes such as age.

This model involved representing three types of contact networks at two distinct time points. The three networks represented passenger-passenger, passenger-crew, and crew-crew contacts. We modeled these as three overlapping networks with a shared node set but differing edges (instead of one large network) to provide maximal flexibility in model parameterization and intervention design. The three modeled networks were also doubled to represent a “pre-lockdown” and “post-lockdown” composition. Although the core network features remained the same, the density and determinants of the network structure varied between these time points.

Conceptually, the 6 network models are defined as follows:

- Passenger-Passenger Network
  - Pre-Lockdown
    - Contacts between passengers, with most contacts occurring with passenger in same cabin. Average daily degree of 5.
    - Contacts prohibited with crew members in this network.
  - Post-Lockdown
    - All passenger-passenger contacts limited to within-cabin. Same within-cabin daily degree (average degree of 1) but no contacts with passengers outside of cabin.
    - Contacts prohibited with crew members in this network.
- Passenger-Crew Network
  - Pre-Lockdown
    - Contacts between passengers and crew, with an average daily degree of 8.

        - 50% of contacts restricted to passenger-crew pairs within same ship sector.
        - No contacts within person type permitted.
    - Post-Lockdown
        - Contacts limited to 2 daily visits to each cabin (for cleaning and meal services)
        - 98% of contacts restricted to passenger-crew pairs within the same ship sector.
- Crew-Crew Network
    - Pre-Lockdown
        - Contacts between crew, with an average daily degree of 10.
        - Contacts prohibited with passengers in this network.
    - Post-Lockdown
        - Contacts between crew, with an average daily degree of 2.
        - 98% of contacts restricted to crew-crew pairs within same ship sector.
        - Contacts prohibited with passengers in this network.

Algorithmically, we implemented the swap of network models from pre-lockdown to post-lockdown by implementing a deterministic time step at which the appropriate network model was selected as input for the simulation.

2.2 Statistical Representation of Contact Networks

Exponential-family random graph models (ERGMs) provide a foundation for statistically principled simulation of local and global network structure given a set of target statistics from empirical data. Social contacts were modeled using modeled using cross-sectional ERGMs.(3) This allowed for more flexibility in relational dissolution than temporal ERGMs, in which this is a stochastic process. Repeated contacts within the same dyads (e.g., passenger cabinmates) were allowed through mixing constraints in the cross-sectional network composition.

Formally, our statistical models for relational dynamics can be represented as a set of six equations for the conditional log odds (logits) of relational existence at time *t*:

$$logit\left(P\left(Y_{ij,t<15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{pp}{}'\partial\left(g_{pp}(y)\right) \quad \text{passenger-passenger, pre-lockdown}$$

$$logit\left(P\left(Y_{ij,t\geq15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{pp}{}'\partial\left(g_{pp}(y)\right) \quad \text{passenger-passenger, post-lockdown}$$

$$logit\left(P\left(Y_{ij,t<15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{pc}{}'\partial\left(g_{pc}(y)\right) \quad \text{passenger-crew, pre-lockdown}$$

$$logit\left(P\left(Y_{ij,t\geq15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{pc}{}'\partial\left(g_{pc}(y)\right) \quad \text{passenger-crew, post-lockdown}$$

$$logit\left(P\left(Y_{ij,t<15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{cc}{}'\partial\left(g_{cc}(y)\right) \quad \text{crew-crew, pre-lockdown}$$

$$logit\left(P\left(Y_{ij,t\geq15}=1\middle|\, Y_{ij,t}^{C}\right)\right) = \theta_{cc}{}'\partial\left(g_{cc}(y)\right) \quad \text{crew-crew, post-lockdown}$$

where:

- $Y_{ij,t}$ = the relational status of persons *i* and *j* at time *t* (1 = in relationship/contact, 0 = not).

- $Y_{ij,t}^{C}$ = the network complement of *i,j* at time *t*, i.e. all relations in the network other than *i,j.*
- $g(y)$ = vector of network statistics in each model (the empirical statistics defined in the tables above).
- θ = vector of parameters in the model.

For $g(y)$ and θ, the subscript indicates the contact network type. For $Y_{ij,t}$ the subscript differentiates the pre- and post-lockdown times corresponding to day 15. The recursive dependence among the relationships renders the model impossible to evaluate using standard techniques; we use MCMC in order to obtain the maximum likelihood estimates for the θ vectors given the $g(y)$ vectors.

Converting the statistics into our fully specified network models consists of the following steps:

1. Construct a cross-sectional network of 3711 persons with no contacts (an empty network).
2. Assign persons demographics (age) based on ship census data, as well as a passenger type (corresponding to passenger or crew). For passengers, individuals were assigned a cabin number (and thus cabin mate). Both passengers and crew were assigned a sector on the ship to which the cabin and crew were assigned.
3. Calculate the target statistics (i.e., the expected count of each statistic at any given moment in time) associated with the terms in the existence model.
4. Estimate the coefficients for the existence model that represent the maximum likelihood estimates for the expected cross-sectional network structure.

Steps 1–4 occur within the *EpiModel* software and used the ERGM methods therein. They are completed efficiently by the use of an approximation in Step 4 (4). During the subsequent model simulation, we use the method of Krivitsky (5) to adjust the coefficient for the first term in each model at each time step, in order to preserve the same expected mean degree (relationships per person) over time in the face of changing network size and nodal composition. At all stages of the project, simulated partnership networks were checked to ensure that they indeed retained the expected cross-sectional structure and relational durations throughout the simulations.

3 MODEL CALIBRATION

We used Bayesian approaches to define a select set of model parameters with uncertain values, construct prior distributions for those parameters, and fit the model to diagnosed SARS-CoV-2 case data to estimate the posterior distributions of those parameter values.

3.1 Calibration Methods

We used Approximate Bayesian Computation with sequential Monte Carlo sampling (ABC-SMC) methods (6, 7) to calibrate \ parameters in which there was measurement uncertainty in order to match the diagnosed cases. The details of ABC depend on the specific algorithm used, but in this case, ABC-SMC proceeded as follows.

For each candidate parameter, θ, to be estimated, we:

1. Sampled a candidate θ^i from a prior distribution $\pi(\theta)$
2. Simulated the epidemic model with candidate value, θ^i.
3. Tested if a distance statistic, d (e.g., the difference between observed HIV prevalence and model simulated prevalence) was greater than a tolerance threshold, ϵ.
    a. If $d > \epsilon$ then discard
    b. If $d < \epsilon$ then add the candidate θ^i to the posterior distribution of θ.
4. Sample the next sequential candidate, θ^{i+1}, either independently from $\pi(\theta)$ (if 3a) or from θ^i plus a perturbation kernel with a weight based on the current posterior distribution (if 3b).

3.2 Justification of Calibration to Cumulative Incidence Data

We calibrated the model to match the target statistics the cumulative positive SARS-CoV-2 diagnoses on the Diamond Princess ship. Given the potential for overestimating the precision of fitted parameters when using cumulative incidence data (8, 9), we experimented with fitting the model to both raw daily cases and cumulative daily cases. While we appreciate the theoretical advantages of fitting to raw cases suggested in this literature, the procedures were not practical here for four reasons.

First, daily case counts were low because the underlying target population on the ship was small. This is in contrast with the modeling work in King (8) and Towers (9), where the target population was country wide and the daily case counts numbered in the hundreds or thousands. Attempting to calibrate our model to raw case counts simply failed because of the noisiness of the data and algorithms.

Second, the observed cases on the Diamond Princess were a function of diagnosis campaigns with relatively wide temporal fluctuation (i.e., there were waves of diagnoses on certain days). This was in contrast to the Ebola case data in King and Towers, where the diagnoses were more slowly ramping up as the outbreak progressed. If we fit to the daily cases in our model, we could end up overfitting our screening rate parameters versus our more parsimonious approach of calibrating periods of screening rates as they increased over the outbreak (see Supplemental Table 1).

Third, in contrast to the compartmental models featured in King and the statistical time-series models in Towers, our individual-based models have inherently more model stochasticity as a function of model structure. Thus, our model prediction intervals reflect the additional uncertainty involved in stochastic outbreaks in small population settings.

Finally, in contrast to both King and Towers, our primary goal was not parameter estimation (e.g., both of those papers used models to estimate R_0) but counterfactual intervention scenario projection. Of course, the uncertainty of our projections is related to the precision of the parameter estimates, but in a much more indirect way than the direct parameter estimation experiments of King and Towers.

3.3 Calibration Results

We calibrated the model to cumulative daily counts (see Supplemental Figure 1) using calibration prior distributions in Supplemental Table 1. Overall, the model fit well to the cumulative data as well as the raw daily case counts. The estimates of the posterior distribution medians and 95% credible intervals are provided in Supplemental Table 1. For primary analyses, we used the maximum likelihood estimates (medians) from the posterior estimates for model selection purposes. For sensitivity analyses (Supplemental Figures 3–5), we sampled from across the posterior distribution to evaluate the correlation between these estimated parameters and cumulative incidence.

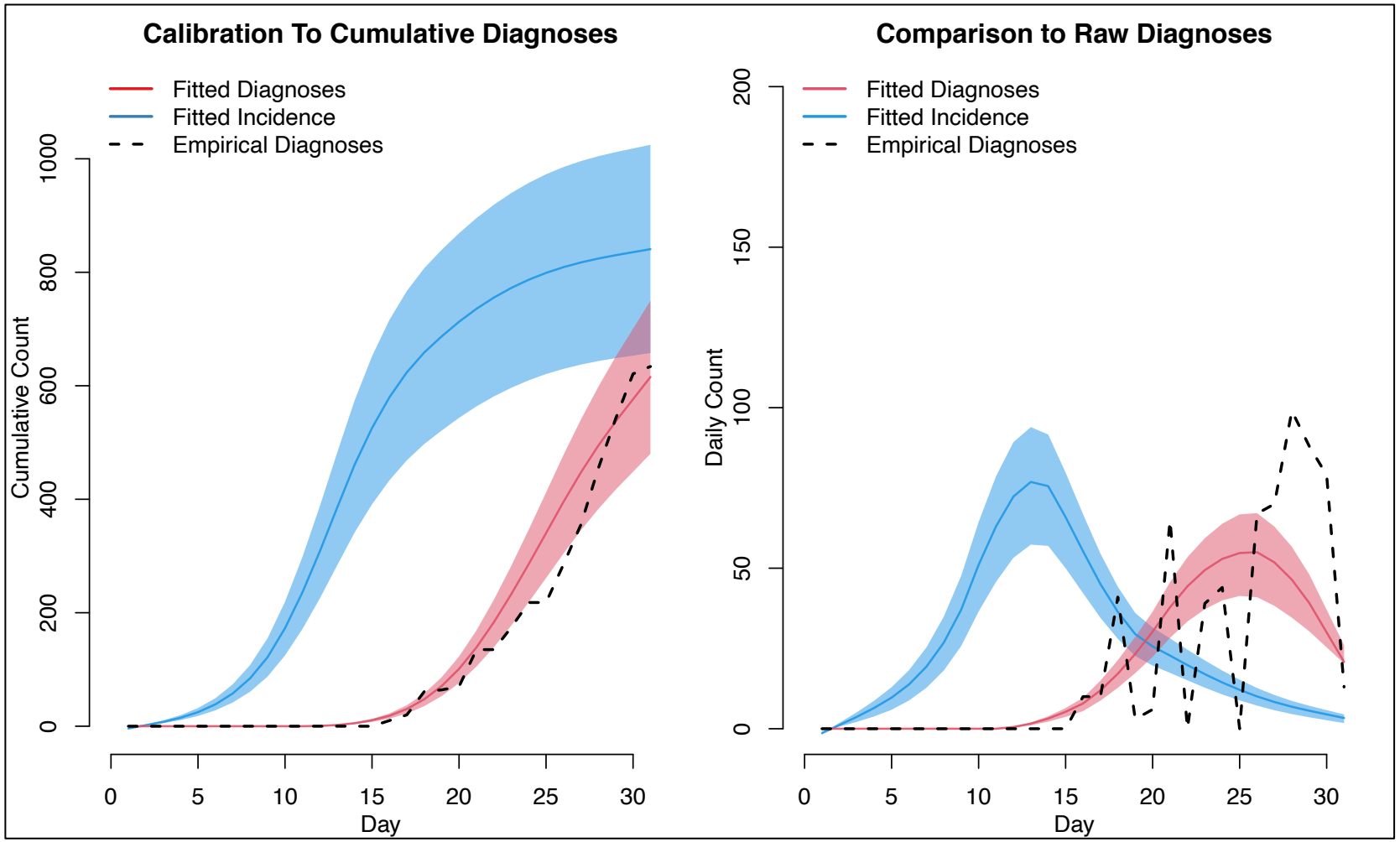
3.4 Post-Calibration Sensitivity Analyses

To evaluate the sensitivity of the primary outcome (cumulative incidence) to the fitted parameters, we conducted a probabilistic sensitivity analysis by sampling from the full posterior distributions of each parameter. This involved drawing from the posterior distributions 10,000 times and recording the cumulative incidence with each parameter set. The bivariate comparisons between each sampled parameter and the outcome are visualized in Supplemental Figures 3–5. The model outcomes are more closely correlated with the infection probability and contact intensity parameters than the screening rate parameters in these bivariate comparisons.

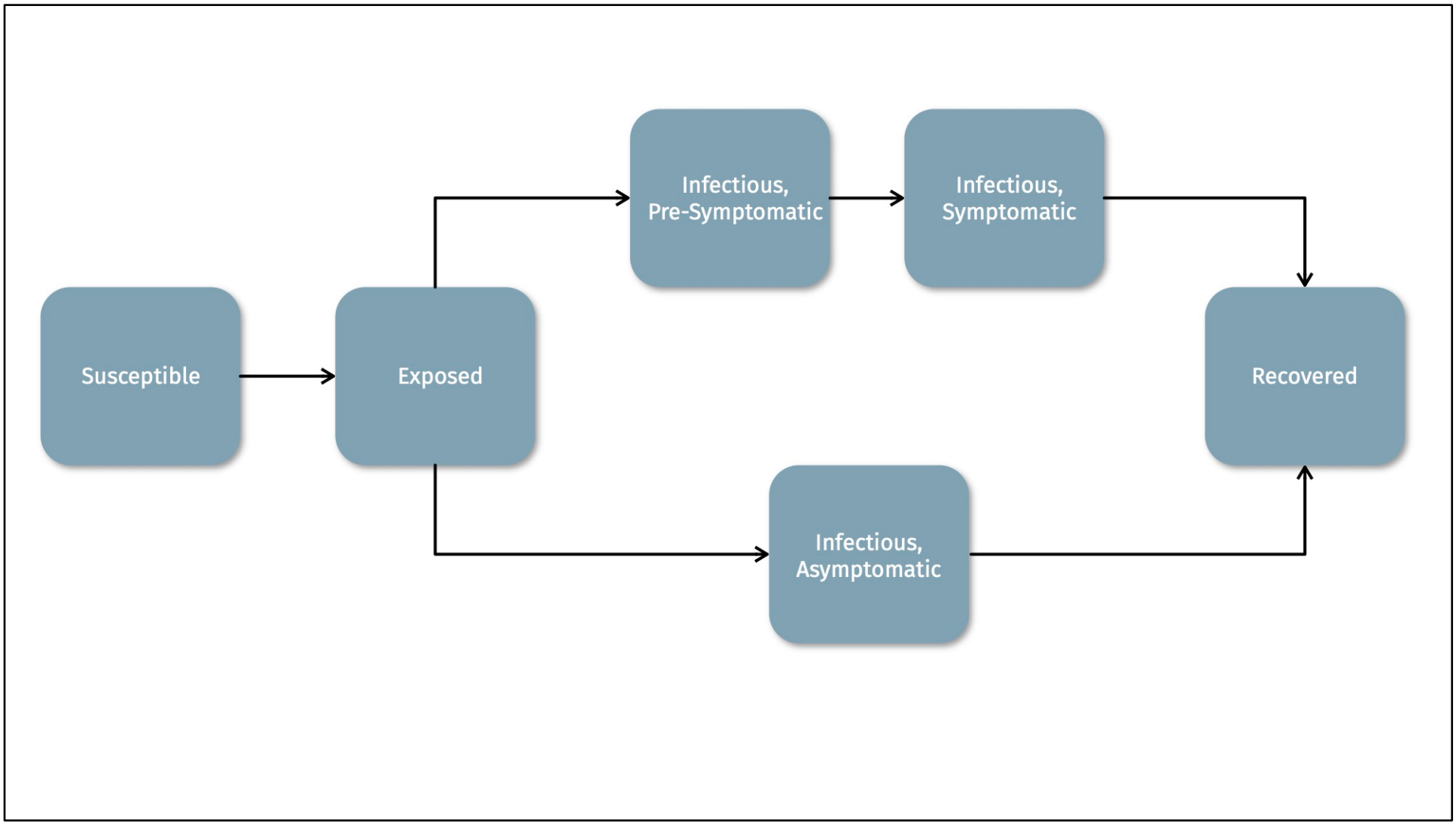
To numerically quantify the independent relationships, we fit a multivariable metamodel with linear regression, with the 10,000 simulations as individual observations. This regression model estimated the relationship between cumulative incidence and symptomatic screening at day 26, asymptomatic screening at day 26, the per-contact infection probability, and the per-dyad exposure intensity. We found no statistically significant relationships with symptomatic screening at day 26 (32.9 fewer cases per 1 unit increase in the screening rate; 95% CI: -167.3, 101.5; $p = 0.63$) or asymptomatic screening at day 26 (144.9 more cases per 1 unit increase in the screening rate; 95% CI: -38.7, 328.6; $p = 0.12$). However, the infection probability (103.3 more cases per 1 percentage point increase in the parameter; 95% CI: 99.8, 106.8; $p < 0.001$) and contact intensity (208.9 more cases per one unit increase in the per-dyad exposures per day; 95% CI: 204.4, 213.6; $p < 0.001$) were strongly associated with cumulative incidence. This multivariable metamodel approach to sensitivity analysis suggests that the intervention results generally may be sensitive to the calibrated parameters related to the force of infection.

SUPPLEMENTAL FIGURES

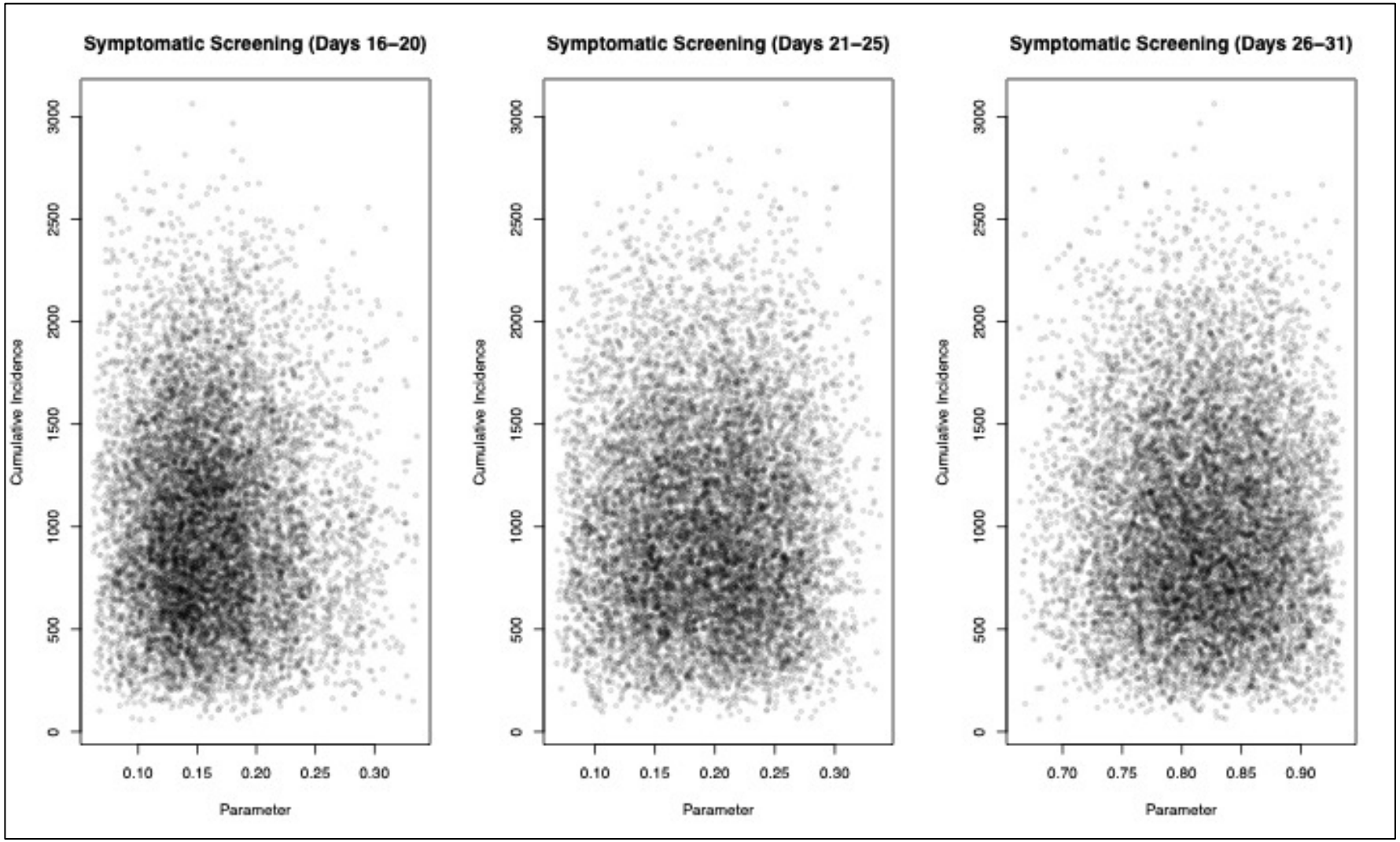
Supplemental Figure 1. Comparison of model calibration to cumulative diagnoses to raw (daily) case counts. As noted above, the daily case counts were noisy due to small population size and temporally varying screening campaigns on the ship, so we elected to calibrate to cumulative diagnoses instead with the caveat that our precision may be overestimated.



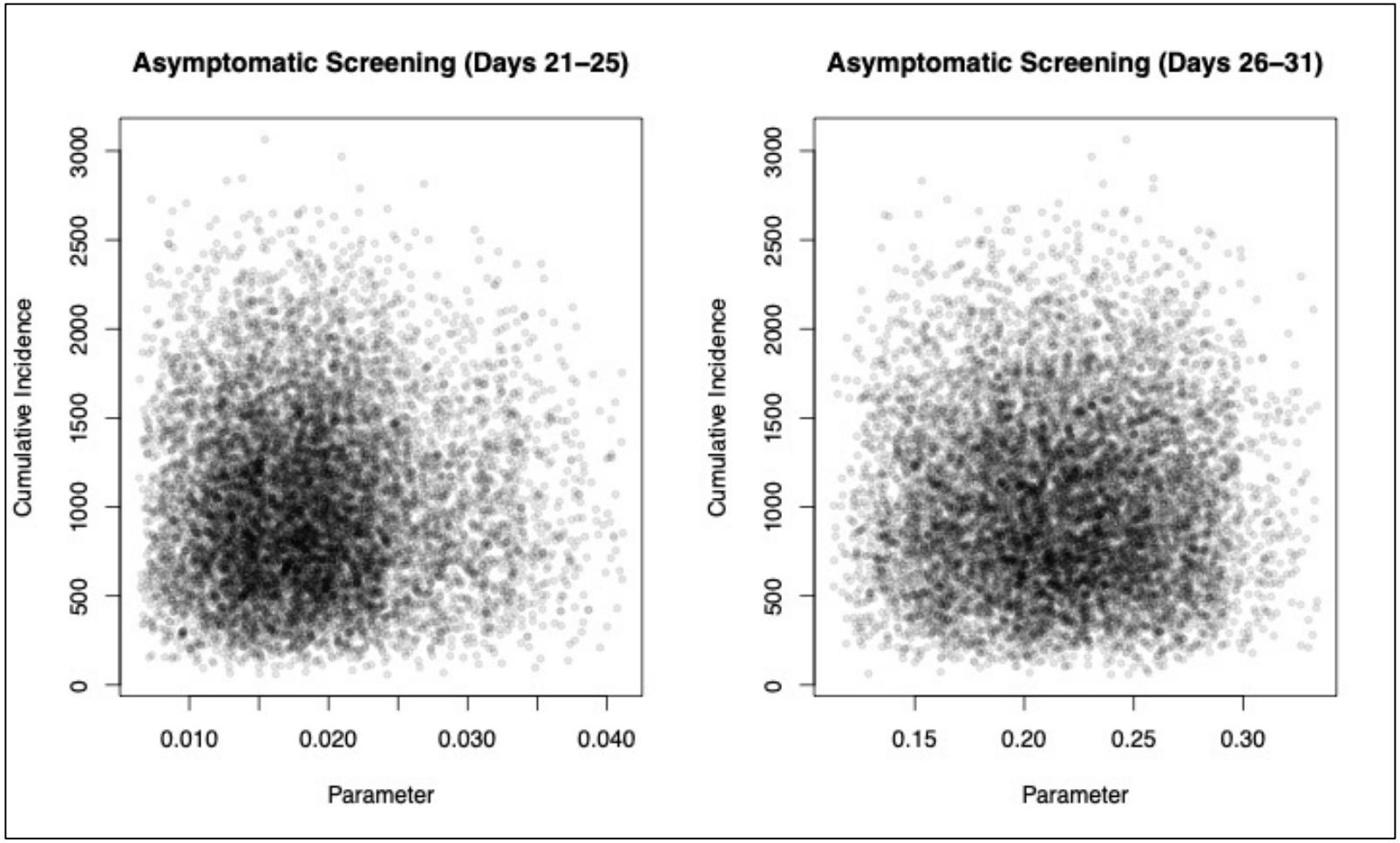
Supplemental Figure 2. COVID-19 transmission and disease progression is represented as transitions from an exposed latent state to either a symptomatic (clinical) or asymptomatic (subclinical) pathway. Transmissibility is reduced within the asymptomatic pathway. Disease-induced mortality occurs within the infectious, symptomatic state only.



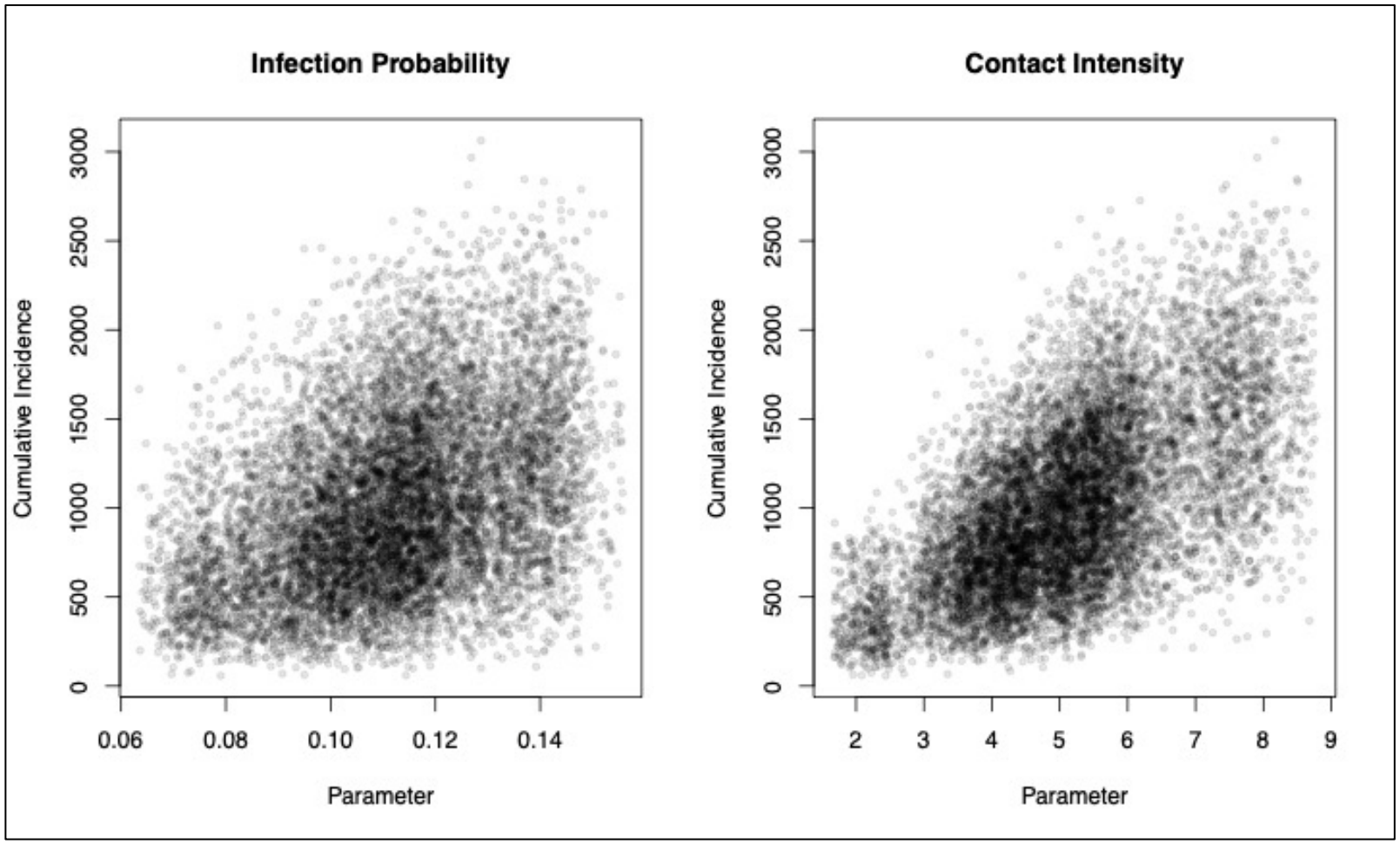
Supplemental Figure 3. Sensitivity analysis of relationship between symptomatic screening rates in three periods and cumulative SARS-CoV-2 incidence.



Supplemental Figure 4. Sensitivity analysis of relationship between asymptomatic screening rate in two periods and cumulative SARS-CoV-2 incidence.



Supplemental Figure 5. Sensitivity analysis of relationship between infection probability per contact and cumulative incidence and contact intensity (number of exposures per day per dyad) and cumulative SARS-CoV-2 incidence.



SUPPLEMENTAL TABLES

Supplemental Table 1. Calibrated Model Parameters

Parameter	Uniform Prior Bounds	Posterior Median (95% Credible Intervals)
Transmission probability per contact	5% – 15%	11.1% (7.4%, 14.2%)
Passenger-Passenger within Dyad Exposures	1 – 9	5.12 (2.31, 7.88)
Screening Rates (Symptomatic Cases)	Days 1–15: 0 Days 16–20: 0.1 – 0.3 Days 21–25: 0.1 – 0.3 Days 26–31: 0.7 – 0.9	Days 1–15: 0 Days 16–20: 0.154 (0.102, 0.264) Days 21–25: 0.193 (0.109, 0.278) Days 26–31: 0.818 (0.715, 0.893)
Screening Rates (Asymptomatic Cases)	Days 1–15: 0 Days 16–20: 0 Days 21–25: 0.01 – 0.3 Days 26–31: 0.05 – 0.15	Days 1–15: 0 Days 16–20: 0 Days 21–25: 0.018 (0.010, 0.032) Days 26–31: 0.219 (0.159, 0.278)

Supplemental Table 2. Primary Model Parameters

Parameter	Value	Source
Transmission probability per contact	11%	Kraay 2020 (10); Fitted
Relative reduction in transmission with PPE	40%	Chu 2020 (11)
Passenger-Passenger Daily Mean Degree, Pre-Lockdown	5	Rocklov 2020 (12); Xue 2020 (13)
Passenger-Passenger Proportion of Network Degree within Cabin, Pre-Lockdown	20%	Moriarty 2020 (14); Assumed
Passenger-Passenger Daily Mean Degree, Post-Lockdown	1	Moriarty 2020 (14); Rocklov 2020 (12)
Passenger-Passenger Proportion of Network Degree within Cabin, Post-Lockdown	100%	Moriarty 2020 (14); Assumed
Passenger-Crew Daily Mean Degree, Pre-Lockdown	8	Rocklov 2020 (12); Xue 2020 (13)
Passenger-Crew Proportion of Network Degree within Same Sector, Pre-Lockdown	50%	Moriarty 2020 (14); Assumed
Passenger-Crew Daily Mean Degree, Post-Lockdown	2	Moriarty 2020 (14); Rocklov 2020 (12)
Passenger-Crew Proportion of Network Degree within Same Sector, Post-Lockdown	98%	Moriarty 2020 (14); Assumed
Crew-Crew Daily Mean Degree, Pre-Lockdown	10	Rocklov 2020; Xue 2020
Crew-Crew Daily Mean Degree, Post-Lockdown	2	Moriarty 2020; Rocklov 2020
Crew-Crew Proportion of Network Degree within Same Sector, Post-Lockdown	98%	Moriarty 2020 (14); Assumed
Passenger-Passenger within Dyad Exposures	5.1 per day	Fitted
Passenger-Crew within Dyad Exposures	1 per day	Assumed
Crew-Crew within Dyad Exposures	1 per day	Assumed
Within Dyad Exposure Rate Reduction Following Positive Diagnosis	0.1 multiplier	Moriarty 2020 (14); Chu (11); Assumed
Proportion Symptomatic	10–19 years: 40% 20–29 years: 25% 30–39 years: 37% 40–49 years: 42% 50–59 years: 51% 60–69 years: 59% 70–79 years: 72% 80+ years: 76%	Davies 2020 (15)
Duration of Latent Period	4 days	Davies 2020 (15)
Duration of Preclinical Infectious Period	1.5 days	Davies 2020 (15)
Duration of Clinical Infectious Period	3.5 days	Davies 2020 (15)

Duration of Subclinical Infectious Period	5 days	Davies 2020 (15)
Natural Mortality Rate	Yearly age-specific rate 0 to 100 years	Global Burden of Disease (16)
COVID-Related Mortality (Multiplier on natural mortality)	180	Manually calibrated
Screening Rates (Symptomatic Cases)	Days 1–15: 0 Days 16–20: 0.162 Days 21–25: 0.191 Days 26–31: 0.817	Fitted
Screening Rates (Asymptomatic Cases)	Days 1–15: 0 Days 16–20: 0 Days 21–25: 0.019 Days 26–31: 0.216	Fitted
PCR Test Sensitivity	80%	Lopman 2020 (17)
Number of Ship Passengers	2,666	Moriarty 2020 (14)
Number of Crew	1,045	Moriarty 2020 (14)

Supplemental Table 3. Impact of Network Isolation Timing, With and Without Personal Protective Equipment (PPE), on COVID-19 Incidence and Mortality at 1 Month

Scenario	Cumulative Incidence			Cumulative Mortality		
	Total	NIA[1]	PIA[2]	Total	NDA[3]	PDA[4]
	Median (95% SI)	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*
Base Isolation Scenario						
Day 15 (with PPE)	948.0 (388.0, 1534.2)	–	–	10.0 (3.0, 20.0)	–	–
Varying Network Isolation Time (with PPE)						
Day 1	15.0 (5.0, 32.0)	931.5 (928.0, 935.0)	98.4 (98.3, 98.4)	0.0 (0.0, 1.0)	10.0 (10.0, 10.0)	100.0 (100.0, 100.0)
Day 5	38.0 (12.0, 80.0)	909.0 (903.5, 914.0)	96.0 (95.9, 96.1)	0.0 (0.0, 2.0)	10.0 (10.0, 10.0)	100.0 (100.0, 100.0)
Day 10	221.0 (91.0, 418.1)	715.0 (704.0, 726.0)	76.0 (75.4, 76.5)	2.0 (0.0, 7.0)	8.0 (8.0, 8.0)	77.8 (77.8, 78.6)
Day 20	2225.5 (1328.0, 2866.1)	-1265.2 (-1287.5, -1243.0)	-132.2 (-135.6, -128.6)	23.0 (11.0, 36.0)	-13.0 (-13.0, -13.0)	-127.3 (-133.3, -122.2)
Day 25	3205.5 (2410.6, 3465.0)	-2224.0 (-2239.0, -2208.0)	-232.6 (-235.9, -228.8)	31.0 (18.0, 43.0)	-20.0 (-21.0, -20.0)	-200.0 (-209.1, -196.4)
None	3522.0 (3298.0, 3600.0)	-2557.0 (-2567.5, -2547.0)	-269.4 (-271.6, -267.3)	32.0 (19.0, 45.0)	-22.0 (-22.0, -21.0)	-212.5 (-220.0, -208.3)
Varying Network Isolation Time (no PPE)						
Day 1	28.0 (8.0, 67.0)	918.0 (912.5, 923.0)	97.0 (96.9, 97.1)	0.0 (0.0, 2.0)	10.0 (10.0, 10.0)	100.0 (100.0, 100.0)
Day 5	62.0 (19.0, 136.1)	881.0 (874.5, 887.5)	93.3 (93.2, 93.5)	0.0 (0.0, 3.0)	9.0 (9.0, 10.0)	100.0 (100.0, 100.0)
Day 10	315.5 (121.0, 560.1)	625.5 (614.0, 638.0)	66.5 (65.8, 67.2)	3.0 (0.0, 8.0)	7.0 (7.0, 7.0)	72.7 (71.4, 75.0)
Day 15	1112.5 (490.0, 1755.1)	-151.5 (-171.5, -132.5)	-16.0 (-18.4, -13.8)	11.0 (3.0, 22.0)	-1.0 (-1.0, 0.0)	-6.7 (-9.1, 0.0)
Day 20	2336.0 (1402.0, 2928.1)	-1380.5 (-1400.5, -1358.5)	-144.0 (-147.4, -140.5)	23.0 (11.0, 37.0)	-13.0 (-13.0, -13.0)	-129.7 (-133.4, -124.0)
Day 25	3228.0 (2520.6, 3481.0)	-2254.5 (-2271.0, -2240.0)	-236.0 (-239.4, -232.7)	31.0 (17.0, 45.0)	-21.0 (-22.0, -21.0)	-209.5 (-216.7, -200.0)
None	3520.0 (3255.9, 3603.0)	-2556.5 (-2566.0, -2547.5)	-269.5 (-271.8, -267.0)	32.0 (19.0, 45.0)	-22.0 (-22.0, -21.0)	-214.8 (-222.2, -210.0)

[1] Number of infections averted relative to base scenario

[2] Percent of infections averted relative to base scenario

[3] Number of COVID-related deaths averted relative to base scenario

[4] Percent of COVID-related deaths averted relative to base scenario

Supplemental Table 4. Directionality of Transmission and Contact Intensity Reductions, with Day 15 Network Lockdown and PPE, on COVID-19 Incidence at 1 Month

Scenario	Total	Passenger to Passenger	Passenger to Crew	Crew to Passenger	Crew to Crew
	Cumulative Incidence	Cuml. Incid.	Cuml. Incid.	Cuml. Incid.	Cuml. Incid.
	Median (95% SI)	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*
With Contact Intensity Reductions, Network Lockdown, and PPE at Day 15					
Base Scenario					
No Intensity Reduction	933.5 (366.0, 1556.2)	551.0 (213.9, 941.0)	163.0 (66.0, 265.0)	124.0 (46.0, 211.0)	93.0 (33.0, 175.0)
Varying Passenger-Passenger Contact Intensity					
50% Reduction	862.5 (353.9, 1454.0)	488.0 (203.9, 843.0)	155.0 (67.0, 257.0)	124.5 (47.0, 216.0)	93.5 (29.0, 174.0)
90% Reduction	765.5 (316.9, 1348.0)	401.0 (164.9, 727.0)	145.5 (63.0, 248.0)	122.0 (44.0, 214.0)	90.0 (31.0, 173.0)
100% Reduction	749.0 (297.9, 1255.1)	381.0 (155.9, 677.0)	147.5 (61.0, 241.0)	126.0 (44.0, 208.0)	93.0 (32.0, 168.0)
Varying Passenger-Crew Contact Intensity					
50% Reduction	849.0 (352.9, 1379.1)	545.0 (230.0, 868.0)	125.5 (54.0, 203.0)	87.0 (31.0, 158.1)	90.0 (31.0, 168.0)
90% Reduction	787.0 (332.9, 1346.1)	535.5 (227.0, 899.0)	96.0 (41.0, 173.0)	62.0 (17.0, 130.0)	87.0 (30.0, 170.0)
100% Reduction	744.0 (325.0, 1274.1)	519.5 (225.9, 865.0)	86.0 (37.0, 152.0)	55.0 (17.0, 117.0)	84.0 (29.0, 167.0)
Varying Crew-Crew Contact Intensity					
50% Reduction	897.0 (379.9, 1471.2)	542.0 (220.8, 904.0)	161.0 (70.0, 254.0)	120.0 (48.0, 203.1)	74.0 (23.0, 142.0)
90% Reduction	899.0 (404.0, 1529.2)	558.0 (255.0, 943.2)	165.0 (78.0, 274.0)	118.0 (47.0, 206.0)	61.0 (17.0, 132.0)
100% Reduction	895.5 (362.9, 1459.1)	558.0 (218.0, 909.1)	162.0 (68.0, 263.0)	115.0 (44.0, 200.0)	55.0 (15.0, 119.0)
With Contact Intensity Reductions and PPE at Day 1, and No Network Lockdown					
Base Scenario					
No Intensity Reduction	3222.0 (2839.9, 3385.0)	2311.0 (2091.0, 2402.0)	472.0 (387.9, 526.0)	151.0 (116.0, 191.0)	280.0 (205.0, 335.0)
Varying Passenger-Passenger Contact Intensity					
50% Reduction	1623.5 (783.9, 2241.0)	1012.0 (489.9, 1389.0)	232.5 (110.0, 322.0)	186.5 (85.0, 273.0)	194.0 (81.0, 288.0)
90% Reduction	206.0 (44.0, 471.0)	38.0 (9.0, 85.0)	35.0 (8.0, 75.0)	68.5 (12.0, 170.0)	63.0 (11.0, 150.0)
100% Reduction	109.0 (14.0, 301.1)	0.0 (0.0, 0.0)	19.0 (3.0, 48.0)	46.0 (4.0, 133.0)	42.0 (3.0, 125.0)

Varying Passenger-Crew Contact Intensity					
50% Reduction	2925.0 (2454.8, 3144.1)	2358.0 (2047.9, 2470.0)	298.0 (216.0, 352.0)	48.0 (30.0, 69.0)	218.0 (131.0, 292.0)
90% Reduction	2526.0 (2092.9, 2709.0)	2375.0 (1995.9, 2507.0)	75.0 (46.0, 99.0)	2.0 (0.0, 7.0)	68.5 (23.0, 126.0)
100% Reduction	2375.5 (2042.9, 2498.0)	2375.5 (2042.9, 2498.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
Varying Crew-Crew Contact Intensity					
50% Reduction	3111.5 (2658.0, 3295.0)	2319.0 (2059.8, 2414.0)	518.0 (397.0, 584.0)	131.0 (97.0, 166.0)	139.0 (90.0, 178.0)
90% Reduction	3030.0 (2580.8, 3203.0)	2331.0 (2040.8, 2423.0)	555.0 (403.9, 632.0)	116.0 (87.0, 148.0)	26.0 (14.0, 40.0)
100% Reduction	3000.5 (2621.9, 3192.0)	2324.0 (2077.8, 2428.1)	558.5 (429.9, 650.0)	114.0 (86.0, 143.0)	0.0 (0.0, 0.0)

Supplemental Table 5. Impact of Varying Intensity of Diagnosis-Based Case Isolation, with Asymptomatic Screening Starting at Day 15, Stratified by Network Lockdown and PPE Use, on COVID-19 Incidence and Mortality at 1 Month

Scenario	Cumulative Incidence			Cumulative Mortality		
	Total	NIA[1]	PIA[2]	Total	NDA[3]	PDA[4]
	Median (95% SI)	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*
Network Lockdown and PPE at Day 15						
100% Isolation	928.0 (416.9, 1545.1)	10.0 (-8.5, 30.5)	1.1 (-0.9, 3.3)	10.0 (3.0, 21.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
90% Isolation (Base)	943.0 (411.8, 1556.0)	0.0 (-20.5, 19.5)	0.0 (-2.2, 2.1)	10.0 (3.0, 21.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
75% Isolation	958.5 (431.0, 1525.1)	-5.5 (-23.5, 14.0)	-0.6 (-2.6, 1.4)	10.0 (3.0, 20.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
50% Isolation	953.0 (414.9, 1548.0)	-16.5 (-35.5, 2.0)	-1.8 (-3.8, 0.2)	10.0 (2.0, 21.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
25% Isolation	974.5 (410.0, 1583.0)	-30.0 (-49.5, -9.0)	-3.2 (-5.3, -0.9)	10.0 (3.0, 21.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
No Isolation	960.5 (426.9, 1588.0)	-28.0 (-45.5, -8.0)	-3.0 (-4.9, -0.9)	10.0 (3.0, 21.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
No Network Lockdown or PPE						
100% Isolation	3499.0 (3251.0, 3591.0)	18.0 (14.0, 22.0)	0.5 (0.4, 0.6)	32.0 (19.0, 46.0)	0.0 (-1.0, 0.0)	0.0 (-2.9, 0.0)
90% Isolation (Base)	3516.0 (3288.9, 3603.0)	–	–	31.0 (19.0, 44.0)	–	–
75% Isolation	3544.0 (3373.0, 3617.0)	-27.0 (-30.5, -23.0)	-0.8 (-0.9, -0.7)	32.0 (21.0, 46.0)	-1.0 (-1.0, 0.0)	-2.9 (-3.4, 0.0)
50% Isolation	3578.0 (3420.0, 3632.0)	-59.0 (-62.5, -56.0)	-1.7 (-1.8, -1.6)	33.0 (20.0, 46.0)	-1.0 (-1.0, -1.0)	-3.2 (-3.9, -2.7)
25% Isolation	3601.0 (3492.9, 3644.0)	-81.0 (-84.0, -79.0)	-2.3 (-2.4, -2.2)	32.0 (19.0, 46.0)	-1.0 (-2.0, -1.0)	-3.3 (-5.1, -2.9)
No Isolation	3621.0 (3514.9, 3656.0)	-100.0 (-103.0, -97.0)	-2.8 (-2.9, -2.8)	33.0 (20.0, 45.0)	-1.0 (-2.0, -1.0)	-3.3 (-5.3, -2.8)

[1] Number of infections averted relative to base scenario

[2] Percent of infections averted relative to base scenario

[3] Number of COVID-related deaths averted relative to base scenario

[4] Percent of COVID-related deaths averted relative to base scenario

Supplemental Table 6. Impact of Timing of Mass Asymptomatic Screening and Diagnosis-Based Case Isolation, with No Network Lockdown and Stratified by PPE Use, on COVID-19 Incidence and Mortality at 1 Month

Scenario	Cumulative Incidence			Cumulative Mortality		
	Total	NIA[1]	PIA[2]	Total	NDA[3]	PDA[4]
	Median (95% SI)	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*	*Median (95% SI)*
Varying Timing of Mass Screening (Never PPE)						
Day 1	2286.0 (0.0, 3421.0)	1403.5 (1396.0, 1409.0)	38.0 (37.9, 38.1)	7.0 (0.0, 24.0)	29.0 (28.0, 29.0)	81.2 (80.6, 81.8)
Day 5	2621.5 (16.0, 3353.1)	1070.5 (1067.0, 1074.0)	29.0 (28.9, 29.1)	9.0 (0.0, 23.0)	27.0 (27.0, 27.0)	75.6 (75.0, 76.0)
Day 10	2917.0 (1787.8, 3310.1)	775.0 (772.5, 777.5)	21.0 (20.9, 21.1)	13.0 (4.0, 25.0)	23.0 (22.0, 23.0)	63.6 (62.9, 64.1)
Day 15	2944.5 (2256.8, 3176.1)	746.0 (744.0, 748.0)	20.2 (20.2, 20.3)	18.0 (8.0, 32.0)	18.0 (17.0, 18.0)	50.0 (48.6, 50.0)
Day 20	3102.5 (2588.8, 3360.1)	590.0 (588.0, 591.5)	16.0 (15.9, 16.0)	30.0 (16.0, 45.0)	6.0 (6.0, 7.0)	17.1 (16.1, 18.4)
Day 25	3607.0 (3360.9, 3668.0)	85.0 (84.0, 86.0)	2.3 (2.3, 2.3)	36.0 (24.0, 50.0)	0.0 (-1.0, 0.0)	0.0 (-2.5, 0.0)
Never (Reference)	3692.0 (3679.0, 3699.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	36.0 (25.0, 49.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
Varying Timing of Mass Screening (Always PPE)						
Day 1	1629.5 (0.0, 3013.0)	2012.0 (1998.0, 2023.0)	55.3 (55.0, 55.4)	5.0 (0.0, 20.0)	27.0 (27.0, 28.0)	85.2 (84.5, 85.7)
Day 5	1856.5 (12.0, 2837.4)	1776.0 (1766.0, 1784.5)	48.8 (48.6, 49.0)	6.0 (0.0, 19.0)	26.0 (26.0, 27.0)	81.0 (80.5, 81.5)
Day 10	2240.5 (1058.0, 2815.1)	1395.0 (1387.0, 1402.0)	38.3 (38.2, 38.5)	10.0 (2.0, 20.0)	23.0 (23.0, 23.0)	70.6 (70.0, 71.1)
Day 15	2372.0 (1585.6, 2755.0)	1267.5 (1262.0, 1273.0)	34.8 (34.7, 34.9)	15.0 (5.0, 27.0)	18.0 (17.0, 18.0)	54.3 (53.5, 55.0)
Day 20	2656.0 (1980.9, 3033.0)	983.5 (977.5, 988.5)	27.0 (26.9, 27.2)	26.0 (12.0, 40.0)	7.0 (7.0, 8.0)	22.2 (20.9, 23.3)
Day 25	3354.0 (2831.8, 3537.1)	285.5 (282.0, 290.0)	7.8 (7.8, 7.9)	33.0 (20.0, 47.0)	0.0 (0.0, 1.0)	0.0 (0.0, 2.5)
Never (Reference)	3643.0 (3563.0, 3669.0)	–	–	33.0 (20.0, 45.0)	–	–

[1] Number of infections averted relative to base scenario

[2] Percent of infections averted relative to base scenario

[3] Number of COVID-related deaths averted relative to base scenario

[4] Percent of COVID-related deaths averted relative to base scenario

REFERENCES

1. S. M. Jenness, S. M. Goodreau, M. Morris, EpiModel: An R Package for Mathematical Modeling of Infectious Disease over Networks. *J Stat Softw* **84**, 1–47 (2018).
2. M. S. Handcock, D. R. Hunter, C. T. Butts, S. M. Goodreau, M. Morris, statnet: Software Tools for the Representation, Visualization, Analysis and Simulation of Network Data. *J Stat Softw* **24**, 1548–7660 (2008).
3. D. R. Hunter, M. S. Handcock, C. T. Butts, S. M. Goodreau, M. Morris, ergm: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks. *J Stat Softw* **24**, nihpa54860 (2008).
4. N. B. Carnegie, P. N. Krivitsky, D. R. Hunter, S. M. Goodreau, An approximation method for improving dynamic network model fitting. *J Comput Graph Stat* **24**, 502–519.
5. P. N. Krivitsky, M. S. Handcock, M. Morris, Adjusting for Network Size and Composition Effects in Exponential-Family Random Graph Models. *Stat Methodol* **8**, 319–339 (2011).
6. T. Toni, D. Welch, N. Strelkowa, A. Ipsen, M. P. H. Stumpf, Approximate Bayesian computation scheme for parameter inference and model selection in dynamical systems. *J R Soc Interface* **6**, 187–202 (2009).
7. S. E. Bellan, J. Dushoff, A. P. Galvani, L. A. Meyers, Reassessment of HIV-1 acute phase infectivity: accounting for heterogeneity and study design with simulated cohorts. *PLoS Med* **12**, e1001801 (2015).
8. A. A. King, M. Domenech de Cellès, F. M. G. Magpantay, P. Rohani, Avoidable errors in the modelling of outbreaks of emerging pathogens, with special reference to Ebola. *Proc Biol Sci* **282**, 20150347 (2015).
9. S. Towers, O. Patterson-Lomba, C. Castillo-Chavez, Temporal variations in the effective reproduction number of the 2014 west Africa ebola outbreak. *PLoS Curr* **6** (2014).
10. A. N. M. Kraay, K. Nelson, C. Zhao, J. S. Weitz, B. A. Lopman, Modeling serological testing to inform relaxation of social distancing for COVID-19 control. *medRxiv: The Preprint Server for Health Sciences* (2020) https:/doi.org/10.1101/2020.04.24.20078576.
11. D. K. Chu, *et al.*, Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. *Lancet (London, England)* **395**, 1973–1987 (2020).
12. J. Rocklöv, H. Sjödin, A. Wilder-Smith, COVID-19 outbreak on the Diamond Princess cruise ship: estimating the epidemic potential and effectiveness of public health countermeasures. *Journal of travel medicine* (2020).
13. L. Xue, *et al.*, A data-driven network model for the emerging COVID-19 epidemics in Wuhan, Toronto and Italy. *Math Biosci* **326**, 108391 (2020).
14. L. F. Moriarty, Public health responses to COVID-19 outbreaks on cruise ships—worldwide, February–March 2020. *MMWR. Morbidity and Mortality Weekly Report* **69** (2020).
15. N. G. Davies, *et al.*, Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. *Lancet Public Health* **5**, e375–e385 (2020).
16. GBD 2015 Mortality and Causes of Death Collaborators, Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980-2015: a systematic analysis for the Global Burden of Disease Study 2015. *Lancet* **388**, 1459–1544 (2016).
17. B. Lopman, *et al.*, A modeling study to inform screening and testing interventions for the control of SARS-CoV-2 on university campuses. *Sci Rep* **11**, 5900 (2021).